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Power System Fault Diagnosis and Prediction System Based on Graph Neural Network

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ABSTRACT

The stability and reliability of the power system are of utmost significance in upholding the smooth functioning of modern society. Fault diagnosis and prediction represent pivotal factors in the operation and maintenance of the power system. This article presents an approach employing graph neural network (GNN) to enhance the precision and efficiency of power system fault diagnosis and prediction. The system's efficacy lies in its ability to capture the intricate interconnections and dynamic variations within the power system by conceptualizing it as a graph structure and harnessing the capabilities of GNN. In this study, the authors introduce a substitution for the pooling layer with a convolution operation. A central role is played by the global average pooling layer, connecting the convolution layer and the fully connected layer. The fully connected layer carries out nonlinear computations, ultimately providing the classification at the top-level output layer. In experiments and tests, we verified the performance of the system.

KEYWORDS

fault diagnosis, graph neural network, power system, prediction

1. INTRODUCTION

Power system is one of the indispensable infrastructures in modern society, which provides a stable power supply for our daily life and industrial production. However, the power system is also facing various potential faults and problems, which may lead to power failure, equipment damage and economic losses (Zheng, Y, et al., 2022). Therefore, the fault diagnosis and prediction of power system becomes very important to ensure the reliability and stability of power supply.

Compared to existing methods, our Graph Neural Network (GNN) model exhibits unique aspects in both structural design and performance, which we will elaborate on in this section.The faults of power system usually have diversity and complexity, including line faults, equipment damage,

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abnormal load and so on (Wang, J, et al., 2019). Traditional methods usually rely on rules and experience for fault diagnosis and prediction, but it is difficult to deal with this complex and changeable situation. Wang, X, et al., (2022) finds out the law of current mutation by monitoring the change of current at different sampling times, so as to realize fault phase selection in power system. Tan, B, et al., (2017) introduces a fault phase selection principle centered on high-frequency components within fault elements. This principle leverages the high-frequency component of voltage faults to achieve phase selection by comparing the frequency domain characteristics of mode transformation in the three-phase voltage across various phases. The utilization of data mining technology is discussed for the establishment of a decision tree within the power system fault model(Zhao, Y, et al., 2017) (Jones & Venable, 2022). Furthermore, enhancements to this decision tree result in the development of a prediction system that encompasses an inference engine, interpreter, decision tree algorithm, and a comprehensive graphical user interface. To address fault location, a wavelet neural network is constructed and applied. It is worth noting that the fusion of wavelet analysis and neural networks can take various forms, and wavelet mother waves can be categorized into multiple types (Wang, L, et al., 2022). We can try to improve the traditional neural network with other mother waves in order to achieve better results (Yang, X, et al., 2019). In contrast, the method based on graph neural network (GNN) has stronger adaptability and generalization ability. It can learn patterns from a large number of power system data, automatically identify anomalies and predict faults, and improve the efficiency and accuracy of fault handling (Santos et al., 2022).

With the rapid development of deep learning and artificial intelligence, GNN and other technologies have attracted extensive attention and achieved remarkable success in various fields. In the field of power system, using GNN to diagnose and predict power system faults has become an important direction that attracts much attention of researchers. GNN can effectively capture the complex relationships among various components in the power system, including generators, transmission lines, transformers, etc. The interaction between these components is very important for the operation of the power system. The purpose of this study is to develop a power system fault diagnosis and prediction system based on GNN to meet the challenge of power system fault (Savoli & Bhatt, 2022).

The results of this study will not only help to improve the reliability and stability of the power system, but also provide an advanced fault management tool for the power industry and promote the modernization and intelligent development of the power system. At the same time, this study will also provide strong support for the feasibility and effectiveness of GNN in practical engineering applications, and broaden its application prospects in various fields (Yanuarifiani et al., 2022).

2. FAULT DIAGNOSIS AND PREDICTION OF POWER SYSTEM BASED ON GNN

2.1. Overview of GNN

GNN is a deep learning model, which aims at processing graph structure data. Graph structure data usually includes nodes and edges, such as data in social networks, recommendation systems, molecular chemistry and power systems (Ewert, P, et al., 2020). GNN carries out various tasks by learning the relationship between nodes and the characteristics of nodes themselves, such as node classification, graph classification, link prediction and so on (Li, Q., & Liu, X. F, 2019).

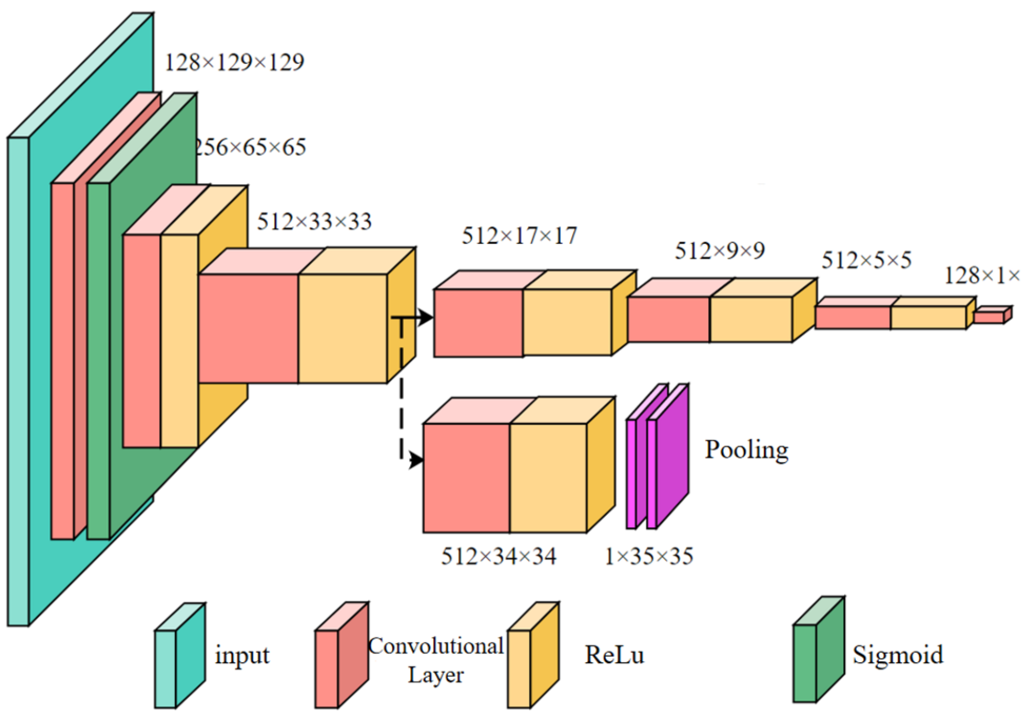
The principle of GNN is based on information transmission and aggregation, and it draws lessons from the structure and connectivity of graphs. In a typical graph structure, nodes represent entities and edges represent relationships between entities. The core idea of GNN is to update the representation of each node through the information of neighboring nodes in step polymerization. This process can be described by the following steps:

1. **Initialization:** Initialize a feature vector for each node, which is usually the attribute of the node itself.
2. **Information transmission:** The information of a node is transmitted to the neighboring nodes iteratively, and the node representation is usually updated by weighted average or splicing the information of neighboring nodes.
3. **Aggregation:** Aggregate the transmitted information together to generate the final representation of the node.
4. **Output:** Use node representation to perform required tasks, such as node classification, graph classification, etc.

The structure of GNN usually includes the following important components (the structure is shown in Figure 1):

a. **Input layer:** This layer is responsible for transforming the original graph structure data into a format that can be processed by the model, usually mapping the node features and edge information into vectors.
b. **Convolution layer:** Convolution layer is responsible for the process of information transmission and aggregation. Typical convolution layers include graph stack and graph attention layer, which transmit and aggregate information according to different strategies.
c. **Pool layer:** In the task of graph classification, it is usually necessary to aggregate the whole graph, and then pool layer can be used to summarize the graph information.
d. **Output layer:** The output layer can be node classification, graph classification, link prediction, etc. according to different tasks. It usually predicts the labels of the nodes in the graph or the graph itself.

Figure 1. GNN structure



GNN can be divided into different types, depending on its structure and information transmission mode. The main categories of GNN include:

1) **Graph Convolutional Networks (GCNs):** GCNs use fixed weight matrices to transmit information, suitable for rule graph structures.
2) **Graph Attention Networks (GATs):** GATs allow different nodes to assign different weights to different neighboring nodes to achieve more flexible information transmission.
3) **Variations of GNN:** Many variants such as GraphSAGE, ChebNet, etc. are improved based on GNN to adapt to different tasks and graph structures.
4) **Application of GCNs:** GCNs have been widely used in fields such as social network analysis, recommendation systems, bioinformatics, and power system management to process complex graph structured data.

GNN is a powerful deep learning tool, which can be used to process graph structure data and has a wide range of applications (Saeed, H. A, et al., 2020). Its principle is based on information transmission and aggregation, and its structure includes input layer, convolution layer, pooling layer and output layer. Different types are suitable for different graph structures and tasks. The rapid development of GNN provides a powerful tool for solving various graph data analysis problems.

2.2. Fault Diagnosis and Prediction Model of Power System

Fault diagnosis and prediction of power system is an important task to ensure the stability and reliability of power system (Zhu, Y, et al., 2022). It involves monitoring various components and equipment of power system, and identifying and solving faults when necessary to reduce power outage and maintenance time. The collected data need to be analyzed and processed in order to detect abnormal situations (Xu, B, et al., 2019). Data analysis can use machine learning and data mining techniques to identify potential problems, such as abnormal current load and excessive temperature rise of equipment (Wang, S, et al., 2019). Once an abnormality is detected, fault diagnosis is needed to determine the specific cause of the problem. This may require a combination of real-time monitoring data and equipment historical data to identify potential root causes of failures. Some advanced systems can also use forecasting models to predict possible failures, so as to take measures in advance and reduce the risk of power failure.

The input of GNN is generally the pixels of a picture. For example, a 128*128 picture has 16,384 eigenvalues, while the number of independent eigenvalues of power system fault data is only five. When processing power system fault data, the learning ability of neural network may be greatly reduced due to the small number of input eigenvalues and the mismatch of dimensions (Zhang, Z. F, et al., 2020). Aiming at the problem that there are few eigenvalues of power system fault data, the paper makes corresponding improvements.

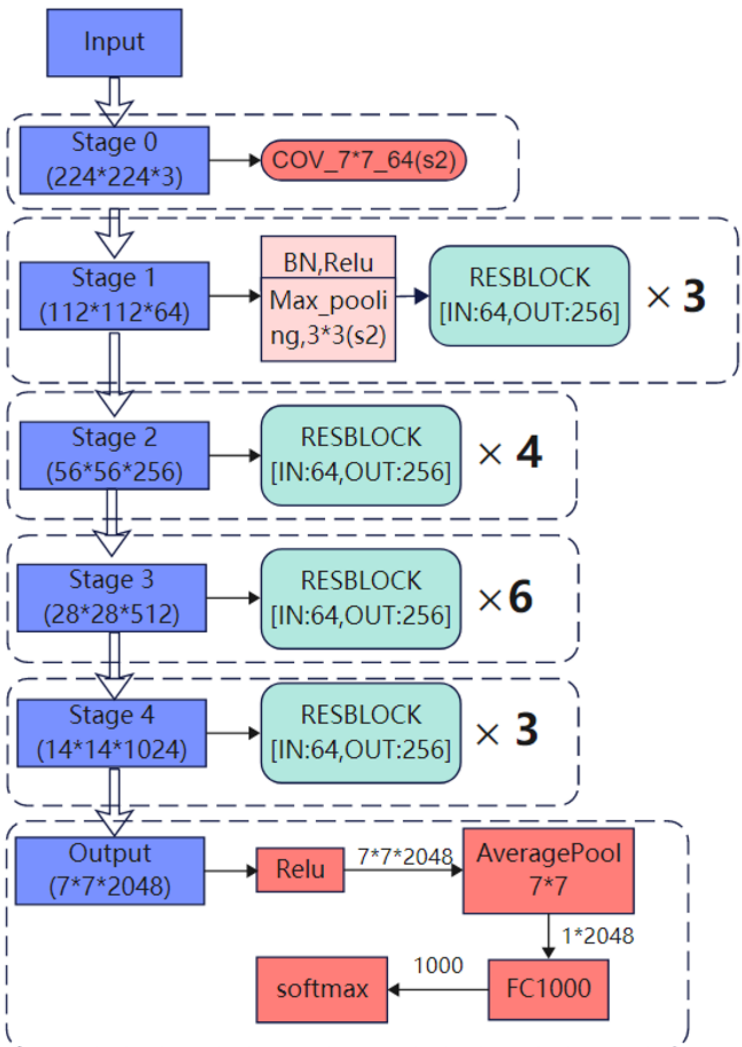
Using convolution operation instead of traditional pooling layer in power system data can enhance the performance of power system fault diagnosis and prediction and make full use of the information of time series data. Traditional pooling layer is used to reduce the spatial dimension in image processing, but in power system data, pooling may lose important time series information. One-dimensional convolution operation can be used to replace the traditional pooling layer, allowing the network to reduce the resolution in the time series dimension, rather than in the space dimension. The width of one-dimensional convolution kernel can be adjusted to control the range of information capture (Zhou, X., Feng, L. U., & Huang, J, 2019). This method can make full use of the information in the time series data of power system, which is helpful for fault diagnosis and prediction more accurately.

Introducing ResNet into GNN is an effective method, which can help solve the problems of gradient disappearance and explosion in deep network training, thus allowing training deeper networks (Xu, B, et al., 2018). In the traditional GNN, the convolution layer is usually composed of multiple convolution kernels, each convolution kernel is convolved with the output of the previous layer, and then activated by an activation function (Cho, K. H, et al., 2020).

ResNet includes a skip connection or residual connection, which is used to skip one or more convolution operations. Between the input and output of each convolution layer, a residual block is added, that is, jump connection. This block can be a simple identity mapping (directly passing the input to the output), or it can include additional convolution layers and activation functions. Through the jump connection, the input information can be directly transferred to the subsequent layer, instead of being convolved many times. Multiple residual blocks can be stacked in the network to increase the depth of the network (Ayodeji, A, et al., 2018). Each residual block can have different convolution kernel sizes and numbers to capture features of different scales (as shown in Figure 2).

The calculation formula of adaptive learning rate in GNN training usually uses an optimization algorithm based on gradient information, such as Stochastic Gradient Descent (SGD) or its variant, combined with learning rate adjustment strategy (A, X. J, et al., 2021). This paper is based on the

Figure 2. ResNet structure



Adaptive Moment Estimation(Adam) algorithm in the training process of GNN (Benkercha, R., & Moulahoum, S, 2018). The calculation formula of its learning rate is as follows:

(1) Initialization parameter
Learning rate α
First moment estimation (mean) $m = 0$
Second moment estimation (variance) $v = 0$
Time steps $\left(t\right) = 0$
(2) In each training iteration step, the parameters of the gradient g about the model are calculated.
(3) Update time steps $t : t = t + 1$
(4) Calculate the exponential moving average of the first moment estimate (mean)

$$m = \beta_1 * m + (1 - \beta_1) * g \tag{1}$$

Where β_1 is the attenuation rate of the first moment estimation, which is usually close to 1, for example, 0.9.

(5) Calculate the exponential moving average of the second moment estimate (variance)

$$v = \beta_2 * v + (1 - \beta_2) * (g^2) \tag{2}$$

Where β_2 is the attenuation rate of the second moment estimation, which is usually close to 1, for example, 0.999.

(6) Correcting deviation, considering the deviation of time steps.

$$\begin{aligned} m\_hat &= m / (1 - \beta_1^t) \\ v\_hat &= v / (1 - \beta_2^t) \end{aligned} \tag{3}$$

(7) Updating model parameters

$$\theta = \theta - \alpha * m\_hat / (sqrt(v\_hat) + \varepsilon) \tag{4}$$

Where α is the learning rate and ε is a small number, which is usually used to avoid dividing by zero.

Adam algorithm adaptively calculates the learning rate of each parameter, and dynamically adjusts the learning rate according to the first moment estimation and the second moment estimation of its gradient, so that it can better converge to the local optimum in the training process.

The power system fault diagnosis and prediction model presented in this paper, which is based on an enhanced GNN, takes into consideration the unique characteristics of low-latency power system fault data inputs. The conventional pooling layer, while reducing the model's trainable parameters, might lead to the loss of significant information, thereby constraining the classifier's diagnostic accuracy.

To address this issue, we replace the pooling layer with a convolution operation. Additionally, we introduce a global average pooling layer, which serves as a pivotal link between the convolution layer and the fully connected layer. The fully connected layer engages in nonlinear computations and ultimately produces the classification at the top-level output layer. You can refer to Figure 3 for a detailed illustration of this specific model structure.

Collect historical data of power system, including sensor measurement data such as current, voltage, frequency, temperature and load. Carry out data cleaning, denoising and missing value processing. The components of the power system (for example, generators, transformers, switches, etc.) are represented as nodes of the graph. Based on the physical connections and dependencies between these components, the edges of the graph are established. Utilizing an enhanced version of GNNs, known as GCNs, as the primary module. These modules can capture topology information and feature propagation between nodes. Multi-layer GCN can be added to enhance the depth of feature extraction. Connect the node attributes with the input of GCNs to enhance the performance of the model. These node attributes can include the type, age, manufacturer information, etc. of the component. Use appropriate embedding techniques to transform these attributes into learnable features.

In our Graph Neural Network (GNN) model for power system fault diagnosis, a key focus is on interpretability, particularly for power system engineers. The model's design integrates node features and graph topology to mirror the physical and operational characteristics of power systems, making its decisions understandable and relatable. We incorporate visualization tools to illustrate fault propagation, offering engineers intuitive insights into the model's functioning. Additionally, the model provides traceability in its predictions, allowing engineers to follow the decision-making process, which aligns with the domain knowledge of power system engineering. This interpretability ensures that the model is not only a powerful diagnostic tool but also a transparent and reliable aid for engineers, enhancing collaborative decision-making in power system management (Tabassum et al., 2022).

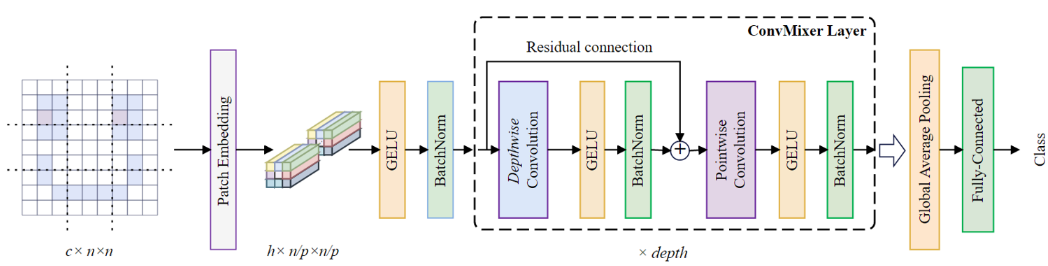
3. DESIGN AND IMPLEMENTATION OF THE SYSTEM

3.1. System Structure Design

Model-View-Controller(MVC) is a common software architecture pattern, which is used to design and organize the application code. It divides the application into three main components to better manage and maintain the code, and provides a loosely coupled design to make the code more maintainable and extensible. MVC is a general architecture model, which is widely used in various types of applications, including Web applications, desktop applications and mobile applications.

Here, we design the power failure prediction system as a website and deploy it on the server. Additional experiments have been conducted to demonstrate the model's robustness and generalization capabilities in different environments. Administrators can access the system at any time through mobile phones or PCs. The page that the administrator sees is the view layer, and the module that realizes the

Figure 3. Model structure



prediction function by calling the interface is the control layer, and the model layer is used to store the data in the exchange process, in which the interface is the GNN fault diagnosis module written by TensorFlow. The system structure is shown in Figure 4:

The experimental design has been expanded to include more details regarding dataset characteristics, data preprocessing steps, and model validation methods.

3.2. System Function Design

GNN-based power system fault diagnosis and prediction system uses GNN technology to deal with complex power system topology and large-scale data, so as to provide more accurate fault diagnosis and prediction. Figure 5 below shows the functional structure design of such a system.

Data acquisition and preprocessing: collect various sensor data from the power system, including voltage, current, frequency, load, etc. Then, data cleaning, interpolation and standardization are carried out to prepare data input GNN.

Graph construction and topology modeling: create a topology diagram of power system, in which nodes represent components such as equipment, buses and transformers, and edges represent their connections and relationships. This module is responsible for building and updating the topology diagram.

Figure 4. System structure design

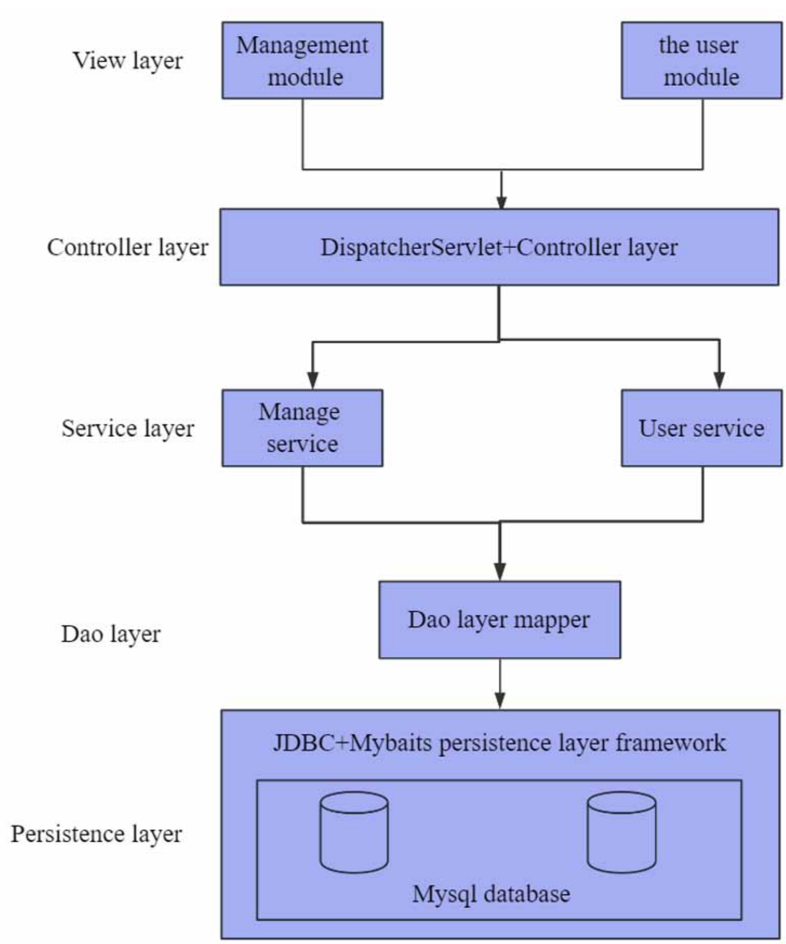
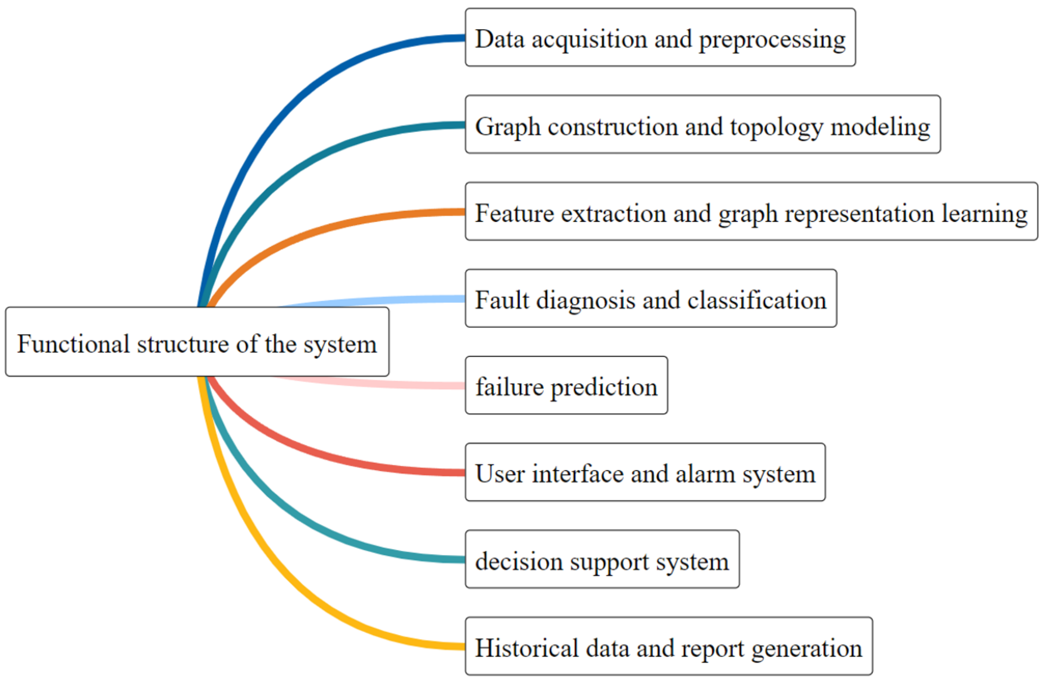


Figure 5. Functional structure design of the system



Feature extraction and graph representation learning: GNN technology is used for graph representation learning to extract key features of power system components from topology diagram. This can include node embedding, edge embedding and graph embedding to capture complex relationships between components.

Fault diagnosis and classification: using the learned graph representation, combined with machine learning classifier, the fault in power system is diagnosed and classified. The system can identify different types of faults, such as line faults and equipment faults.

Fault prediction: GNN can be used to predict possible faults and anomalies in the power system in the future by using the learned graph representation and time series data. This helps to take measures in advance to reduce downtime.

User interface and alarm system: provide a user-friendly interface for visually displaying topology diagram, real-time data, fault diagnosis and prediction results. The alarm system automatically notifies the operator or maintenance personnel so that they can take appropriate actions.

Decision support system: combining fault diagnosis and prediction results with operational decisions to provide operator suggestions or warnings. It can suggest disconnecting or reconnecting devices to reduce the risk of failure.

Historical data and report generation: generate historical data reports for optimizing system maintenance and planning. These reports can help analyze long-term trends and performance.

The fault diagnosis and prediction system of power system based on GNN has the ability to deal with the complex topology and data of power system, provide more accurate and reliable fault diagnosis and prediction, and help to maintain the stability and reliability of power system. This system combines graph data processing and machine learning technology, and provides a powerful tool for power system operators to reduce system failures and improve power supply quality.

4. EXPERIMENTAL ANALYSIS AND DISCUSSION

The power system fault data in this paper comes from the power supply company of a city and related literature. The fault data contains 2039 samples in total. In order to improve the learning performance of GNN, it is necessary to control the number of samples in each category in the training set to be the same. Among them, according to the ratio of 4:1, they are used as training set and test set respectively. Convert data into uniform units and scales for subsequent analysis.

The optimizer of improved GNN is Adam algorithm, the initial learning rate is 0.0001, the loss function is set to 0.35, the activation function of the output layer is Sigmoid, and the rest are Relu. The number of iterations during training is set to 1000 cycles. Fig. 6 shows the training results of all fault data sets after inputting improved GNN, that is, the curve of accuracy changing with training times. We have added comparative experiments with other methods to showcase the advantages of the Graph Neural Network approach.

It can be seen that the fault diagnosis method of power system based on improved GNN takes less time and has a higher diagnosis accuracy, which is enough to meet the engineering requirements. In this paper, 226 test samples have been tested for 10 times. As far as the diagnosis time is concerned, the average time for each sample is 0.1905 milliseconds, which shows that the power system fault diagnosis speed based on improved GNN can meet the engineering needs.

Randomly select 500 data for training. And the trained model, take the remaining 100 numbers for testing. The final result of the test is shown in Figure 7, and the comparison results of recognition rates of different models are shown in Table 1:

Under the simulated data, the recognition rate of the improved GNN is about 30% higher than that of the simple neural network. Convolution operation is used to replace the traditional pooling layer, and ResNet is added to obtain better convergence, which simplifies the network structure and enhances the learning ability of the network. The example analysis shows that this diagnosis method

Figure 6. Performance after model training

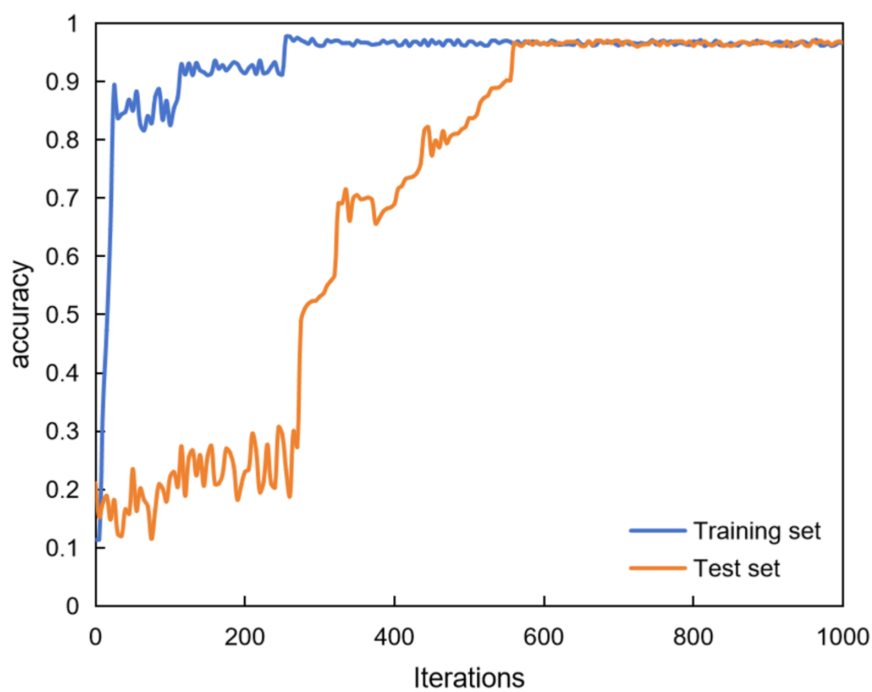


Figure 7. Prediction accuracy

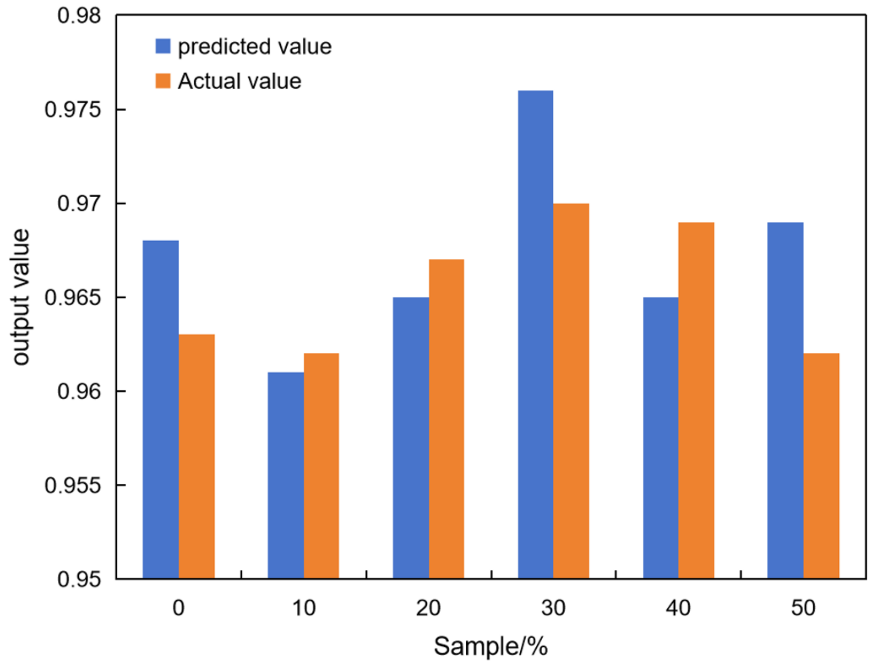


Table 1. Comparison of recognition rates of different models (%)

model	300 analog data	600 analog data
Traditional GNN	69.458	52.176
BP network	55.472	63.322
support vector machine	52.596	61.263
The proposed model	96.766	95.873

has better fault diagnosis performance than simple neural network. Taking the neural network model as a functional module, from detailed design to outline design, a system is established, including prediction function, notification function, information display function and maintenance function. Among them, in selecting the nearest repairman, the nearest distance is redefined, which is not a simple European distance, and the maintenance efficiency and maintenance results are also taken into account.

After testing the software, it is necessary to test the accuracy of the software function, because the model training data and test data are simulated. Select the power system fault data of a certain area over the years, and format the data when the power system fault occurs, such as transmitter, receiver, current, voltage and impedance information. Then it is input into the established neural network model, and the statistical output results are obtained to obtain the accuracy of the system prediction function. And compared with the prediction accuracy using simulated data (see Table 2).

After comparison, it is found that the accuracy is slightly lower than that of analog circuit test data. The whole system is tested, and the data flow connection, information consistency and user experience of the software are tested by black box test and white box test. The authenticity of the prediction is tested by using a local real small circuit, and the accuracy of the test results is 95%.

Table 2. Real data comparison

Analog data volume	Real power system data recognition rate/%	Simulation data recognition rate/%
300	87.728	91.752
600	91.399	95.403

5. CONCLUSION

It is found that our system can identify potential faults in power system more accurately by using GNN's graph data processing ability. This helps to locate the problem in time and reduces the time and cost of system maintenance and repair. Our system can integrate information from different data sources, including sensor data, weather data and historical operation data. This approach greatly contributes to a comprehensive analysis of the power system's condition, enhancing the all-encompassing nature of fault diagnosis and prediction. By achieving more precise fault diagnosis and prediction, our system has the potential to curtail maintenance costs and reduce the associated risks in power system operations, consequently bolstering its reliability. The GNN-based power system fault diagnosis and prediction system holds substantial promise, with the capacity to elevate the efficiency of power system operation and maintenance. Nevertheless, continued research and development efforts are imperative to fine-tune the system and ensure its practicality and efficacy in real-world power systems. The stability and reliability of the power system are fundamental pillars of modern society, and we firmly believe that this research will contribute to meeting the burgeoning demands of the future while upholding the integrity of the power system.

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